A test of the 'one-point method' for estimating maximum carboxylation capacity from field-measured, light-saturated photosynthesis

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Summary

- Simulations of photosynthesis by terrestrial biosphere models typically need a specification of the maximum carboxylation rate (V_{cmax}). Estimating this parameter using A-C_i curves (net photosynthesis, A, vs. intercellular CO_2 concentration, C_i) is laborious, which limits availability of V_{cmax} data. However, many multi-species field data sets include A_{sat} (net photosynthetic rate at saturating irradiance at ambient atmospheric CO_2 concentration) measurements, from which V_{cmax} can be extracted using a "one-point method".
- We used a global data set of A-C_i curves (564 species from 46 field sites, covering a range of plant functional types) to test the validity of an alternative approach to estimate V_{cmax} from A_{sat} via this "one-point method".
- If leaf respiration during the day (R_{day}) is known exactly, V_{cmax} can be estimated with an $r^2 = 0.98$ and root mean squared error (RMSE) of 8.19 μmol m^{-2} s^{-1}. However, R_{day} typically must be estimated. Estimating R_{day} as 1.5% of V_{cmax}, we found that V_{cmax} could be estimated with an $r^2 = 0.95$ and RMSE of 17.1 μmol m^{-2} s^{-1}.
- The one-point method provides a robust means to expand current databases of field-measured V_{cmax}, giving new potential to improve vegetation models and quantify the environmental drivers of V_{cmax} variation.
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Keywords: V_{cmax}, photosynthesis, one-point method, A_{sat}, A-C_i curve, R_{day}.

Introduction

Photosynthesis is a primary driver of the terrestrial carbon cycle (Prentice *et al*., 2001; Beer *et al*., 2010) and accurate modelling of this process is critical for projecting the response of the terrestrial biosphere to environmental change (Friedlingstein *et al*., 2014). Terrestrial biosphere models (TBMs; including ecosystem, land surface and vegetation models) almost universally simulate photosynthesis following the leaf biochemical model of Farquhar *et al*., (1980), or a variant of this approach (e.g. Collatz *et al*., 1991). This approach relies on the accurate estimation of two key model parameters: V_{cmax}, the maximum carboxylation rate, and J_{max}, the maximum rate of electron transport (von Caemmerer, 2000). A third term, triose-phosphate utilisation, is often ignored as it is thought to seldom limit photosynthesis under field conditions (Sharkey *et al*., 1985; but see Ellsworth *et al*., 2015). In many cases both V_{cmax} and J_{max} scale linearly with leaf nitrogen (N) (Field & Mooney, 1986; Hirose & Werger 1987), although the scaling with N can differ among biomes (e.g. Meir *et al*., 2002; Domingues *et al.,* 2015). V_{cmax} and J_{max} also tend to be closely correlated, a fact that some models exploit by assuming J_{max} can be determined through a fixed relationship with V_{cmax} (see Niinemets & Tenhunen (1997) for a critique), or, at least, assuming that variation in the two properties is tightly coordinated (Chen 1993; Maire *et al*., 2012). Nevertheless, V_{cmax} and J_{max} both vary considerably among species (up to a 30-fold variation; Walker *et al*. 2014; Ali *et al*. 2015), among and within plant functional types (PFTs) (Wullschleger 1993; Kattge *et al* 2009; Maire *et al*., 2012; Ali *et al* 2015), and within individual species. Given this large variability it is perhaps unsurprising that TBMs have demonstrated considerable sensitivity in simulated carbon fluxes due to uncertainty in these parameters (Bonan *et al*., 2011; Piao *et al*., 2013). As a consequence these parameters are often used as a method of model "tuning" to obtain more accurate fluxes (which we consider as obtaining the 'right answer for the wrong reasons'), rather than as a means of characterising a PFT-specific trait (Rogers, 2014).

Traditionally, the photosynthesis model parameters V_{cmax} and J_{max} have been estimated by fitting the Farquhar *et al*., (1980) photosynthesis model directly to photosynthetic CO_2 response curves, where photosynthesis is measured at several CO_2 concentrations and under saturating irradiance (net photosynthesis, A (μmol m^{-2} s^{-1}), vs. intercellular CO_2 concentration, C_i (μmol mol^{-1}); so-called A-C_i curves). However, accurately determining these parameters from such measurements is not a straightforward process (see Long & Bernacchi *et al*., 2003). Firstly, A-

C_i data are time consuming to collect: each CO_2 response curve may take an hour to set up and measure, particularly in stressed plants where stomatal closure may even prohibit such measurements. Secondly, a number of competing methods exist for fitting the data (Sharkey *et al*., 2007; Dubois *et al*., 2007; Patrick *et al*., 2009; Gu *et al*., 2010; Feng & Dietze, 2013) and, depending on the chosen method, parameter estimates may vary even for the same datasets (Miao *et al*., 2009; Niinemets *et al*., 2009). Many individual experimental studies tend to focus just on a small number of species and, more often than not, they concern plants grown and measured in controlled environments (laboratory or glasshouse). As a result, compared to many plant traits, there is a general paucity of field-measured V_{cmax} and J_{max} data, which likely undermines the accuracy of model simulations of terrestrial photosynthesis. The largest data compilations to date included V_{cmax} data based on A-C_i curve analysis for 127 species (Ali *et al*., 2015), 114 species (Walker *et al*., 2014), 130 species (Sun *et al*., 2014) and 109 species (Wullschleger 1993), but it is unclear what proportion of these data were for field-grown plants, nor what total species number these represent, with many individual datasets appearing in more than one compilation. Currently in the TRY database (www.try-db.org; accessed 7 July 2015) there are geo-referenced V_{cmax} data for 353 species (of which *c.* 250 were obtained from A-C_i curves).

In contrast to the relatively limited number of field-measured A-C_i curves, there is a plethora of net photosynthesis measurements obtained in the field at ambient [CO_2] and at saturating irradiance (A_{sat}) – e.g. 1500 species were included in the compilation by Maire *et al*., (2015; dataset assembled in 2008), the TRY database currently contains geo-referenced photosynthesis data for 2192 species (8522 individual observations), and in recent years there have been a number of large field campaigns, from which the data are yet to make it into these types of databases. Together, these A_{sat} data represent species from large parts of the globe, and all PFTs (Kattge *et al* 2011), but are currently left out of analyses of V_{cmax}. By virtue of their global coverage, analyses of A_{sat} have included quantification of latitudinal, climate- and soil-related trends, including modulation of relationships between A_{sat} and other leaf traits (Reich *et al*., 1997, 2009; Wright *et al* 2005; Ordonez & Olff 2013; Maire *et al*., 2015). When corresponding values of C_i and leaf temperature are reported with each A_{sat} measurement, and if one assumes: (1) that photosynthesis at saturating irradiance is Rubisco-limited (rather than being limited by RuBP regeneration); and (2) that the value of leaf mitochondrial respiration in the light (i.e. 'day' respiration, R_{day}) can be estimated, then the V_{cmax} value required to

support the observed rate of A_{sat} can be estimated. This estimated quantity is hereafter referred to as $\hat{V}_{cmax}$, and the method as the "one-point method" (Wilson *et al* 2000). However, whether A_{sat}-dependent estimates of $\hat{V}_{cmax}$ are an accurate reflection of the V_{cmax} values obtained from full A-C_i curves remains uncertain. In the absence of measurements of C_i, values may be estimated from data reported for stomatal conductance and ambient [CO_2]. Values for R_{day} may be estimated from either a relationship with dark respiration, R_{dark}, or by assuming a relationship with $V_{cmax;}$ see below).

Although several studies have indeed done this – used measurements of A_{sat} and associated parameters to estimate $\hat{V}_{cmax}$ (Niinemets *et al*., 1999; Wilson *et al*., 2000; Kosugi *et al*., 2003; Grassi *et al*., 2005; Kattge *et al*., 2009; Uddling *et al.,* 2009; Niinemets *et al*., 2015) – a thorough examination of the issues associated with this approach has not been made. That said, preliminary tests of the approach were encouraging. For five tree and five understory species Wilson *et al*., (2000) estimated V_{cmax} from A-C_i curves as well as from independent measurements of the assimilation rate, C_i at the ambient external CO_2 concentration (360 μmol mol^{-1}) and a constant value of R_{day} (~0.5 μmol m^{-2} s^{-1}). The two sets of estimates were tightly correlated (r^2 = 0.97) with an intercept not statistically different from zero, but with a small bias in the slope (1.08). Grassi *et al*., (2005) demonstrated that this method could be used to accurately estimate V_{cmax} for three deciduous forest species (r^2 = 0.97; slope = 0.96). Given the global coverage of A_{sat} data, there could be great potential for deriving $\hat{V}_{cmax}$ from datasets such as that of Maire *et al*. (2015), or the TRY database (Kattge *et al.,* 2011), providing a means to dramatically expand the species- and geographic coverage of V_{cmax} estimates from field-grown plants in global databases. Nevertheless, employing this approach may result in errors and/or bias, which leads to the question and the focus of this study: "*How robust is the so-called one-point method for estimating* V_{cmax}?" Errors in estimation are principally likely to occur if (1) the biochemical limitation to A_{sat} is not Rubisco activity or (2) if the estimate of R_{day} is biased (Figure 1).

We tested how well the one-point method works, by estimating V_{cmax} from complete A-C_i response curves and comparing these values with V_{cmax} estimated using the one-point method applied to the A_{sat} data extracted from these curves. To this end, we compiled 1,394 A-C_i

response curves, from 564 species. These data represent by far the largest compilation of field-measured photosynthetic CO_2-response data to date. These data are taken from all vegetated continents – from the Arctic to the tropics – and so represent a broad spread of site climates (Fig S1). Using this dataset, we sought to test the following hypotheses:

i. That under ambient CO_2 and saturating irradiance, A_{sat} is normally Rubisco-limited, or co-limited by Rubisco and electron transport (a requirement for the one-point method to be valid). There are environmental conditions where this is less likely to be true, leading to the following additional hypotheses:
    a. In mesophytic leaves growing in wet and/or humid environments, the effective operational C_i for leaves is likely to be high, meaning, the leaf is more likely to be electron-transport limited, and thus $\hat{V}_{cmax}$ values are more likely to be underestimated.
    b. The J_{max} to V_{cmax} ratio at 25 °C has been found to decline with increasing growth temperature (Dreyer et al. 2001; Medlyn *et al*., 2002a; Kattge & Knorr, 2007; Lin *et al*., 2013). As a result, the leaf is more likely to be electron-transport limited at higher growth temperatures; thus we also hypothesise an under-estimation of V_{cmax} at higher growth temperatures.
ii. Estimates of V_{cmax} would in general be less accurate for leaves operating at low A_{sat} and/or low g_s because the cumulative effect of errors in the various underlying assumptions would contribute to a lower signal-to-noise ratio.
iii. Uncertainties in R_{day} can contribute to greater bias for estimating V_{cmax} using the one-point method.

In this study we provide a thorough analysis of the one-point method for estimating carboxylation capacity from point measurements of light-saturated photosynthesis, and indicate the conditions under which it works best or may be subject to greater errors. Our primary purpose is to find out whether it would be viable to markedly expand plant trait databases of maximum carboxylation capacity, V_{cmax}, by supplementing those data acquired from A-C_i curves with values derived from A_{sat} by the one-point method.

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Material and Methods

Datasets

We collated 1,394 A-C_i curve measurements from 564 C3 species (91 families) and 46 field sites across various ecosystems, including Arctic tundra, boreal and temperate forest, semi-arid woodlands and tropical forest (Table 1, Figure S1). In most cases measurements were made using the LI-6400 portable photosynthesis system (LI-COR, Inc., Lincoln, NE, USA), except for one data set obtained in Estonia which was measured using a customised open system (Niinemets *et al.,* 1998). We selected data where measurements were first conducted at ambient CO_2 concentration (360–400 µmol mol^{-1}, depending on the year of collection) and saturating irradiance conditions (photosynthetic photon flux density, PPFD, between 1000 and 2000 µmol m^{-2} s^{-1}). The measurements then progressed through a series of step-wise changes in CO_2 concentration spanning sub-ambient (40–400 µmol mol^{-1}) and super-ambient saturating CO_2 concentration (typically > 700 µmol mol^{-1}). During each A-C_i response curve measurement, leaf temperatures were maintained close to the site ambient temperature, ranging from 6 to 40°C. Any measurements obtained which did not follow this protocol, e.g. in cases where the first measurement was recorded at sub-ambient CO_2, were not used in our analyses.

Estimation of apparent V_{cmax}, J_{max} and R_{day} from A-C_i response curves

We first estimated apparent V_{cmax}, J_{max} and R_{day} by fitting each field-measured A-C_i curve using the C_3 photosynthesis model of Farquhar *et al*., (1980). Several different estimates for the temperature-dependence of K_c, the Michaelis constant for CO_2 (µmol mol^{-1}), K_o, the Michaelis constant for O_2 (mmol mol^{-1}), and Γ^*, the CO_2 compensation point in the absence of mitochondrial respiration (µmol mol^{-1}), can be found in the literature (Badger & Collatz, 1977; Jordan & Ogren, 1984; Brooks & Farquhar, 1985, Bernacchi *et al.,* 2001; Crous *et al.,* 2013). We chiefly use values taken from Bernacchi *et al.* (2001), hereafter denoted B01, in common with many TBMs. To test whether the choice of values for these parameters affects the success of the one-point method, we also used two alternative sets of these parameters, namely those advanced by Badger & Collatz (1977) (denoted BC77) and Crous *et al.,* (2013) (denoted C13): see Table 2 for details. The Γ^* temperature dependencies of tobacco (B01) and eucalypt (C13) represent two extremes of the most and least temperature-sensitive Γ^* responses respectively,

using *in vivo* gas exchange methods (Crous, unpublished data). To contrast with *in vitro* methods, we also considered the temperature response of Γ^* in *Atriplex glabriuscula* (BC77).

The intercellular concentration of oxygen (O_i) was assumed to be 210 mmol mol^{-1} for all data collected at sea level. In other datasets, O_i, C_i, and Γ^* were corrected for the effect of elevation on partial pressure by multiplying by the observed pressure readings and correcting units to µbar, mbar and mbar, respectively. For calculations with the B01 and C13 temperature dependencies, K_o and K_c were converted to units of µbar and mbar, respectively. This was done by assuming that the original measurements were obtained at an average atmospheric pressure of 987 mbar in Urbana, Illinois (von Caemmerer *et al*., 2009). K_o and K_c values from BC77 were simply converted from concentration to partial pressures assuming a standard pressure of 1011.35 mbar.

We assumed an infinite mesophyll conductance (g_m); therefore the estimated V_{cmax} and J_{max} values should be regarded as *apparent* values (Evans 1986; Sun *et al*., 2013), as generally used in TBMs and reported in most of the ecophysiological literature. A closer match to *in vitro* enzyme activity of Rubisco can be obtained by considering the mesophyll conductance to CO_2 to the sites of carboxylation (Flexas *et al*., 2007; Rogers *et al*., 2001); however, as g_m values are available for so few of the sampled species, we assumed that C_i is equal to C_c, the CO_2 concentration at the chloroplast. The C_i at which photosynthesis is co-limited by both carboxylation and RuBP regeneration was calculated for each A-C_i curve based on the apparent V_{cmax}, J_{max} and R_{day} using the C_3 photosynthesis model. As the temperature responses of V_{cmax}, J_{max} and R_{day} are not the focus of our study, we did not adjust the estimated parameter values to a standard temperature. Therefore, all the parameters were estimated at their corresponding measured leaf temperatures. All parameter fits were carried out using the Levenberg–Marquardt least squares approach (Levenberg, 1944; Marquardt, 1963); the source code is freely available from GitHub (De Kauwe *et al*. 2015). Of the 1,394 measured A-C_i curves, the data used to estimate V_{cmax} were screened to exclude "bad" measurement curves based on the traditional A-C_i fitting approach, "bad" being defined as: (i) if the first obtained measurement was at an ambient CO_2 concentration < 300 or > 400 µmol mol^{-1}; (ii) if the fitted function had $r^2 < 0.9$; or (iii) if the relative error of fitted V_{cmax} values is > 40%. After screening this resulted in 1318 measurements; filtering criteria (i), (ii) and (iii) removed ~4%, 1% and 1%,

respectively The fitting method used makes no assumption about the C_i value at which the leaf transitions between carboxylation and RuBP regeneration limitations (C_i transition point), but it does use a hyperbolic minimum function to smooth the transition between the carboxylation and RuBP regeneration limitations (Kirschbaum & Farquhar, 1984).

$\hat{V}_{cmax}$ *estimation from the one-point method*

The main underlying assumption of the one-point method is that leaf net photosynthesis under ambient CO_2 and saturated irradiance conditions is limited by Rubisco carboxylation rather than by RuBP regeneration (Wilson *et al.,* 2000; Rogers & Humphries, 2000). As such, $\hat{V}_{cmax}$ can be estimated from the carboxylation-limited portion of the photosynthetic-CO_2 response curve, given by:

$$\hat{V}_{cmax} = (A_{sat} + R_{day}) \frac{(C_i + K_m)}{(C_i - \Gamma^*)} \quad (1)$$

where K_m is the Michaelis-Menten constant, given by:

$$K_m = K_c \left(1 + \frac{O_i}{K_0}\right) \quad (2)$$

Kc, Ko (and Γ^*) were estimated following the equations in Table 2. We used the first measurement point of each A-C_i curve as the A_{sat} value required to estimate V_{cmax}. One difficulty with this approach is that it requires an estimate of R_{day}. In the first instance we used the fitted value for R_{day} obtained from the A-C_i curve (hereafter called 'known' R_{day}). This approach may be viewed as a "best-case" test of the method, since these values will not be known when only A_{sat} is measured. In order to estimate V_{cmax} in the situation where R_{day} is not known, we assumed that R_{day} was 1.5% of V_{cmax} (hereafter called 'estimated' R_{day}), following Collatz *et al*., (1991). Under this assumption, the estimation equation is:

$$\hat{V}_{cmax} = A_{sat} \left(\frac{C_i + K_m}{C_i - \Gamma^*} - 0.015\right) \quad (3)$$

The fixed proportion between R_{day} and V_{cmax} was proposed by Collatz *et al*. (1991) to hold at 25°C. We further assumed that this ratio would remain constant with varying leaf temperature, thus assuming similar temperature dependences for R_{day} and V_{cmax}. This assumption is reasonable because leaf respiration and V_{cmax} both typically have increasing temperature

dependences with Q10 values close to 2 at temperatures up to 35°C (Collatz *et al*., 1991; Medlyn *et al.*, 2002; Atkin *et al.*, 2015).

Assessing the robustness of the one-point method

We compared $\hat{V}_{\mathrm{cmax}}$ values to V_{cmax} values estimated from each full A-C_{i} curve in order to assess the performance of the one-point method. We also analysed the residuals as a function of a range of variables to identify the circumstances under which the method is most (or least) successful.

As there were 1318 data points we opted in a number of comparison plots to (i) group (colour) species by PFT and also (ii) to bin these data (Fig. 2, 4, 5, 7, S1 and S2). Binning the data (with all values within a 'bin' being averaged out to a single value), allows us to better visualise the underlying main trends in large datasets, rather than being distracted by the small number of points towards the edges of any bivariate distribution. Regression lines however were fitted to raw data, not to the binned data. Bin sizes are shown in all figure captions.

Other datasets

Using 0.5° resolution Climate Research Unit climatology data (CRU CL1.0; New *et al*. 1999) over the period 1961 to 1990, we derived for each site: mean annual temperature (MAT; a proxy for growth temperature); mean annual precipitation (MAP); a moisture index (representing an indirect estimate of plant water availability, calculated as the ratio of mean annual precipitation to the equilibrium evapotranspiration as described in Gallego-Sala et al., 2010); and the number of growing degree days above 0 and 5 degrees C, respectively. We also obtained site elevation estimates from data from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model Version 2 (GDEM V2) at 1.0° resolution.

Results

328 The C_i transition point of each A-C_i curve was located by fitting both the Rubisco-limited and
329 RuBP-limited net CO_2 assimilation rates and then identifying the point at which the two
330 limitations intersected (transition point) (Fig. 2a). In our dataset *c*. 94 % of the measured A_{sat}
331 values were found to be Rubisco-limited under saturated irradiance and ambient CO_2. This
332 result supports the key underlying assumption of the one-point approach: that in field datasets
333 at current C_a and (importantly) at light saturation, carboxylation usually limits A (hypothesis i).
334 Among the wide range in estimated transition points there was some distinct patterning
335 according to plant functional type (PFT; Fig 2b); namely, higher median transition points for
336 evergreen needleleaf species than in broadleaf species (whether evergreen or deciduous; post
337 hoc Tukey tests: $p < 0.001$), and higher median transition points in herbaceous species than in
338 deciduous shrubs (post hoc Tukey test: $p = 0.08$) (note the deciduous needleleaf forests PFT
339 only has three sample curves).

340

341 *Known R_{day}*

342 When R_{day} was known, $\hat{V}_{cmax}$ values were in excellent agreement with V_{cmax} derived from
343 traditional A-C_i curve fitting (Fig. 3). Across all species, $\hat{V}_{cmax}$ values were estimated with a
344 positive bias of 0.99 μmol m^{-2} s^{-1}; $r^2 = 0.98$; root mean squared error (RMSE) = 8.19 μmol m^{-2} s^{-1}. Error and bias varied somewhat among PFTs (bias = -4.02 – -2.26 μmol m^{-2} s^{-1}; $r^2 > 0.95$;
346 RMSE: 4.33 – 10.34 μmol m^{-2} s^{-1}.) but were still rather modest even in the worst case,
347 deciduous shrubs (RMSE = 10.34 μmol m^{-2} s^{-1}).

348

349 Residuals between V_{cmax} and $\hat{V}_{cmax}$ were examined as a function of several factors, namely:
350 V_{cmax} estimated from traditional A-C_i curves (Fig. 4a), ambient g_s (Fig, 4c), estimated R_{day} (via
351 A-C_i curve; Fig. 4e) and ambient C_i (Fig. 4g); leaf temperature, mean annual temperature (MAT;
352 a proxy for growth temperature) and mean annual precipitation (MAP) (Fig. 5); and a selection
353 of other common indices of site climate (site moisture index, elevation, growing degree days;
354 Figs. S2-3). The plot of residuals against the "true" V_{cmax} values (Fig. 4a) shows considerable
355 scatter in individual $\hat{V}_{cmax}$ values. When using a known R_{day}, this spread in errors largely
356 disappears in the binned data, suggesting that it results from a small number of individual
357 measurements. There was a positive trend in the residuals that indicates increasing error with

increasing V_{cmax} values, but importantly, most (~10 % of binned data) errors are small (within 10%, denoted by dotted lines in Fig. 4a).

We originally hypothesised that we would observe larger biases between $\hat{V}_{cmax}$ and V_{cmax} at high ambient C_i and in species sampled from very wet and/or humid environments, due to a greater stomatal aperture (hypothesis i(a)). When using a known R_{day} our dataset did not support this hypothesis (Fig 4c): at high g_s, there was a weak trend for over-estimation of V_{cmax}, rather than the hypothesised under-estimation expected if the error resulted from being above the operating C_i. Whilst there was a small trend with MAP, the slope was negligible (Fig. 5c) and there were no trends when examining the residuals as a function of C_i (Fig. 4g). We also hypothesised that we might see greater bias at high growth temperatures (hypothesis i(b)). When using a known R_{day}, our results do indeed show a significant trend with increasing MAT (proxy for growth temperature; Fig 5c), and the annual number of growing degree-days (Fig. S3), but again the slope of this trend was negligible. We also hypothesised that we may see larger error (both absolute and relative) in the residuals at low g_s values due to a low signal-to-noise ratio (hypothesis ii). To test this prediction, we divided the measurements into two groups: those at low g_s (<0.2 mol m^{-2} s^{-1}) and those at higher g_s (>0.2 mol m^{-2} s^{-1}). The RMSE was similar in both groups (8.07 µmol m^{-2} s^{-1} vs. 8.37 µmol m^{-2} s^{-1} at low and high g_s, respectively), but the percentage error was greater (8.4% vs. 4.5%), supporting our prediction.

Estimated R_{day}

Errors were noticeably greater when R_{day} was estimated as a fixed fraction of V_{cmax}. Overall (all species) there was a negative bias: -2.2 µmol m^{-2} s^{-1}; r^2 = 0.95; RMSE: 17.1 µmol m^{-2} s^{-1}. When grouping by PFT these errors increased further (biases -8.18 – 10.93 µmol m^{-2} s^{-1}; r^2 > 0.85; RMSE: 8.30 – 26.46 µmol m^{-2} s^{-1}). Examining the residuals between V_{cmax} and $\hat{V}_{cmax}$ as a function of the "true" V_{cmax} values (Fig. 4b) showed a negative trend suggesting an over-estimation of V_{cmax} at higher values. Errors were greatest for species grouped into the deciduous broadleaf forest PFT; here $\hat{V}_{cmax}$ values are systematic over-estimates.

These results provide strong support for the hypothesis that uncertainties in R_{day} would contribute to bias in estimating V_{cmax} values (hypothesis iii). Overall, errors were greater across all comparisons when using an estimated R_{day} compared to errors with a known R_{day}. $\hat{V}_{cmax}$ values also showed a positive trend with increasing R_{day} (Fig. 4f), suggesting a modest but systematic under-estimation of $\hat{V}_{cmax}$ at R_{day} values < 2 μmol m^{-2} s^{-1}, and an over-estimation at higher R_{day} values.

To enable the estimation of V_{cmax} without an independent estimate of R_{day}, we assumed a fixed relationship with V_{cmax} that is commonly used in TBMs. However, there was a strong negative relationship between $V_{cmax} - \hat{V}_{cmax}$ residuals and leaf temperature (Fig. 5b) and a notable positive trend in errors with increasing estimates of R_{day} (Fig. 4f), both of which suggest that the relationship between R_{day} and V_{cmax} is not constant. Figure 6a shows the R_{day}:V_{cmax} ratio obtained from fitting our A-C_i response curves as a function of leaf temperature for the B01 temperature dependencies for K_c, K_o and Γ^*. The data show a strong negative trend with increasing temperature. This strong negative trend arises because the fitted R_{day} values decline with leaf temperature (Fig. 6b), rather than increasing in line with V_{cmax} as we assumed. Figure 6b indicates that fitted R_{day} values commonly hit the lower bound of zero above 25°C. As R_{day} is estimated as the value of A where $C_i = \Gamma^*$, this may indicate that the values of Γ^* used are inappropriate for these datasets.

Sensitivity to temperature dependencies of K_c, K_o and Γ^*

We repeated the exercise of comparing $\hat{V}_{cmax}$ and V_{cmax} using two alternative temperature dependencies of K_c, K_o and Γ^* for the case where R_{day} was estimated (Fig. 7; Figs S4-5). The accuracy of estimated values was largely insensitive to our three tested assumptions. $\hat{V}_{cmax}$ values estimated with the C13 paramaterisation had the lowest RMSE values (average across all PFTs 13.85 μmol m^{-2} s^{-1}) and those estimated with BC77 had the largest (average across all PFTs 15.42 μmol m^{-2} s^{-1}). However, grouping by PFTs, the mean absolute difference between the different parameterisations was small, *c.* 2 μmol m^{-2} s^{-1}. It is also notable that using the BC77 parameterisation resulted in greater errors for herbaceous species, RMSE = *c*. 19 vs. *c*. 11 μmol m^{-2} s^{-1} for B01 and C13 parameterisations. Figures S4-S5 demonstrate that the assumption of a fixed ratio of 0.015 for R_{day}: V_{cmax} is still relatively poor for BC77 and C13

parameterisations, particularly at low leaf temperatures; the approximation is marginally better for the C13 parameterisation, explaining the lower RMSE values obtained with this parameterisation.

Discussion

In this study we have examined an alternative approach to traditional A-C_i curve analysis for estimating V_{cmax}, an approach that holds promise for greatly expanding the set of species represented in global V_{cmax} datasets. One of the principal concerns about the use of this approach has been that typical measurements of A_{sat} may be limited by RuBP-regeneration rates, rather than Rubisco activity, and hence would yield underestimates of V_{cmax}, especially in wet or warm conditions. Here we have demonstrated that, for photosynthesis measurements taken at ambient CO_2 and under saturating irradiance conditions, values are normally Rubisco-limited and as such, $\hat{V}_{\mathbf{cmax}}$ values are in good agreement with V_{cmax} determined from A-C_i curves. Residual analysis when using a known R_{day} did not show any bias in V_{cmax} estimation with environmental conditions such as mean annual temperature or precipitation. As a result, our results suggested that the one-point method is likely to be a robust means to resolve V_{cmax} from light-saturated photosynthesis.

That said, our analysis did identify other, non-trivial sources of error in using the one-point approach. First, we found support for our hypothesis that increased errors would occur at low g_s due to a lower signal-to-noise ratio (hypothesis ii), suggesting that rates of A_{sat} that are not subject to severe stomatal limitation are most suited to this approach. Secondly, poor estimation of the day respiration rate, R_{day}, led to a notable increase in the RMSE of estimates, approximately doubling RMSE from 7.18 to 14.71 μmol m^{-2} s^{-1}. The proportional error in V_{cmax} when estimating R_{day} (i.e. Fig 4b) was on average around 20% for most datasets when grouped by PFT. These errors were larger because we estimated R_{day} using a fixed R_{day}:V_{cmax} relationship, and this relationship did not capture variation in values of fitted R_{day}. There was strong bias at low and high temperatures, leading to a clear pattern in residuals. In addition, there was higher estimation error (V_{cmax} – $\hat{V}_{\mathbf{cmax}}$ residuals) at higher V_{cmax}, higher leaf temperatures or at hotter sites (though it should be noted V_{cmax} is typically greater at higher temperatures), and at either very high or very low R_{day}. Having identified and quantified these apparently systematic biases it would of course then be up to individual researchers using this method to decide for themselves what magnitude of error (or bias) was acceptable for the purpose at hand.

R_{day} is as yet not well understood in terms of responses to environmental variation or temperature dependence and hence is difficult to model (Tcherkez *et al*., 2012; Heskel *et al*., 2013; Way & Yamori 2014). It is widely understood that estimates of R_{day} obtained from A-C_i curves are inaccurate. One reason for the inaccuracy is that the values are extrapolated from small fluxes at low C_i conditions, and hence are subject to noise and possibly gasket-leak effects (Bruhn *et al*. 2002; Hurry *et al*. 2005). In this study we also show that there is a systematic bias in R_{day} estimates with temperature (Figs. 5 and 6), which leads to bias in estimates of $\hat{V}_{cmax}$. This bias could be potentially due to a number of factors. Firstly, fluxes are lower at lower temperature, so errors due to noise may be greater. Secondly, it is likely that our assumptions for the temperature dependence of either, or both, R_{day} and Γ^* are incorrect. Fitted estimates of R_{day} showed either no temperature dependence, or a negative temperature dependence, depending on what Γ^* was assumed (Figs 6, S4 and S5). In contrast, most studies of R_{day} suggest a positive temperature dependence, as is assumed in most TBMs (KC – refs?). The issue may lie with Γ^* : the most widely-used parameterisation for Γ^* (B01) resulted in fitted values of R_{day} going to zero at higher temperatures, suggesting this parameterisation may in fact be too temperature-sensitive for many species. This issue also affects photosynthesis values estimated by TBMs using estimates of V_{cmax} obtained from A-C_i curves, because such models commonly use a fixed ratio for R_{day}:V_{cmax}. The estimates of V_{cmax} are dependent on the fitted values of R_{day} (i.e. our known R_{day}). If models estimate photosynthesis with fitted V_{cmax} but a fixed R_{day}:V_{cmax} ratio, the resulting estimates of photosynthesis will be in error. Addressing this problem requires that we develop better empirical parameterisations of the temperature dependences of both Γ^* and R_{day}, which are applicable across species and climates, rather than the single-species, single-site relationships currently used.

Commented [MD3]: REFs – Kristine? Owen?

An alternative approach to using a fixed R_{day}:V_{cmax} ratio would be to base estimates of R_{day} on measured values of dark respiration rate, R_{dark}. For example, it could be assumed that R_{day} = 0.6 × R_{dark} (Kirschbaum and Farquhar 1984) or, alternatively, one might simply set R_{day} = R_{dark}, as was done by Atkin *et al*., (2015) when employing the one-point method. However, we note that such approaches would still result in errors when estimating $\hat{V}_{cmax}$ because they both assume a similar temperature dependence for R_{day} and R_{dark}, whereas the fitted temperature

503 dependence of R_{day} does not resemble the exponential response typically found for R_{dark} (Figs
504 6, S4 and S5).

505

506 *New research avenues*

507 Despite the error introduced by inaccuracies in R_{day}, the one-point method nevertheless has the
508 potential to provide new insight into variability of V_{cmax} across and within species, PFTs and
509 in relation to other plant traits. Due to logistical constraints, studies measuring V_{cmax} using A-
510 C_i curves typically focus on a relatively small number of species, and are biased towards both
511 controlled environments and temperate regions (e.g. Wullschleger 1993; Kattge *et al*., 2009;
512 Sun *et al*., 2014; Walker *et al*., 2014). The results of this paper suggest that measurements of
513 A_{sat}, which are more readily made on a wide range of species under field conditions, can also
514 be used to estimate V_{cmax} using the one-point method. An expanded global V_{cmax} database would
515 greatly facilitate testing of ecophysiological theories of plant trait distribution based on
516 environmentally driven traits (Verheijen *et al*., 2013, Reich, 2014, van Bodegom *et al*., 2014),
517 trait-trade offs (Wright *et al*., 2010, Reu *et al*., 2011) and optimality concepts (Xu *et al*., 2012;
518 Prentice *et al*., 2014; Wang *et al*., 2014; Ali *et al*., 2015b). Larger datasets for V_{cmax} would also
519 allow insights into the true scaling of photosynthetic capacity with leaf structural and chemical
520 traits, with the caveat that we have identified some systematic biases in the approach,
521 suggesting it would be best to constrain analysis to data < 30°C (Fig 5b).

522

523 From a modelling perspective, additional data would serve to improve the underlying evidence
524 base used to constrain model simulations of photosynthesis. For example, Bonan *et al*., (2011)
525 found that uncertainty due to V_{cmax} was equivalent to uncertainties due to structural errors (e.g.
526 scaling photosynthesis and stomatal conductance from the leaf to the canopy), accounting for
527 a ~30 Pg C year^{-1} variation in modelled gross primary productivity in CLM4. A number of
528 models (e.g. CABLE, JULES, CLM4) assume that the J_{max} parameter and/or the autotrophic
529 respiration are proportional to V_{cmax}. Therefore, this single parameter has a marked impact on
530 modelled carbon flux and improvements in the V_{cmax} parameter have the potential to constrain
531 multiple facets of current TBMs. For example, Dietze *et al*., (2014a) showed that inclusion of
532 even small observational datasets of V_{cmax} could adequately constrain the parameterisation of
533 the Ecosystem Demography (ED2) model across a range of biomes. Furthermore, it is now

commonplace in some modelling studies to simulate vegetation fluxes considering the full uncertainty of key parameters, rather than assuming a PFT can be described by a single value (Ziehn *et al*., 2011; Wang *et al*., 2012).

It should be noted that our analysis calls into question the modelling assumption that J_{max} is proportional to V_{cmax}, as shown by the high variability in C_i transition points observed across our data set (Figure 2). These transition points can be used to estimate the ratio of J_{max} / V_{cmax}. We estimated this ratio at 25°C from the transition points, and found a mean value of 1.9 with a large inter-quartile range, stretching from 1.68 to 2.14. As noted above, there was some difference in the median transition point (and hence J_{max} / V_{cmax} ratio) among PFTs, but the variability within a PFT is considerably larger than between PFTs. While the one-point method can provide insights into variation in V_{cmax}, it does not enable us to develop better parameterisations for other key photosynthetic parameters. There remains a need for full A-C_i curves to also quantify the variability in J_{max} / V_{cmax} ratio, or as an alternative, cluster sampling approaches (e.g. extensively sampling of the photosynthesis-light response curve) as proposed by Dietze (2014b).

There is also the potential for a complementary set of parameter estimates to be obtained through a re-examination of existing A_{sat} datasets. Large quantities of field-measured A_{sat} data currently exist in global databases, for example ~1500 species in Maire *et al*., (2015) and 2192 species in TRY (Kattge *et al*., 2011). By putting together V_{cmax} data derived from A-C_i curves with V_{cmax} values determined from the one-point method (i.e., $\hat{V}_{cmax}$), there is potential to generate a database consisting of data for thousands of species, for many hundred sites around the world. Consistent conversion of A_{sat} to V_{cmax} values in worldwide datasets would be strongly beneficial, enabling a wider characterisation of V_{cmax} variations across the globe, and better quantification of relationships between V_{cmax} and other leaf traits (Walker *et al*., 2014) and with site climate (Ali *et al*., 2015). However, it is important to note that application of the one-point method to these datasets may involve additional sources of error. For example, Kattge *et al.* (2009) estimated $\hat{V}_{cmax}$ using a one-point method applied to A_{sat} data that did not include complementary values of C_i, and thus estimated C_i as a constant fraction (0.8) of C_a. In our dataset, the 25th and 75th quartiles for the C_i:C_a ratio were 0.60 – 0.75; use of a constant value

would thus have introduced considerable additional error. Application of the one-point method to species-mean values of A_{sat} and g_s, such as those collated by Maire *et al*. (2015), would also be subject to systematic error from averaging a non-linear function. Thus, application of the one-point method in these circumstances needs to be done with caution.

This manuscript presents an empirical justification for using the one-point method, which we conclude can be used to estimate accurate values of V_{cmax}, for an estimate that we labelled $\hat{V}_{\mathrm{cmax}}$ for distinction from intensively measured curves. We stress that continued measurement of plant behaviour using detailed A-C_i response curves is still invaluable and, indeed, "best-practice". Fitting the model of Farquhar *et al*., (1980) to data has provided a tried and tested way to evaluate and interpret plant physiological behaviour in the field and lab alike. The one-point method tested here *complements* the traditional approach, potentially allowing us to greatly expand plant trait datasets of maximum carboxylation efficiency.

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All data analysis and plots were written in Python; in particular we made use of the Scipy (Jones *et al*., 2001), LMFIT (Neville *et al*. 2014) and Matplotlib libraries (Hunter, 2007).

620

621 **Figure Captions**

622 Figure 1: Conceptual figure demonstrating how errors could arise when estimating V_{cmax} using
623 the one-point method. When R_{day} is correct (dark yellow point) and A_{sat} is Rubisco limited
624 (black point) V_{cmax} is correctly estimated (dashed purple line). When A_{sat} is RuBP-regeneration
625 limited (blue point) V_{cmax} will be under-estimated (dashed blue line). If R_{day} is over-estimated
626 (green point) V_{cmax} will be over-estimated (dashed green line).

627

628 Figure 2: Relationship between ambient C_i and the C_i value at the transition point obtained
629 from A-C_i curve fitting. In panel (a) data shown are for individual species, but have been
630 grouped (coloured) by plant functional type: EBF - evergreen broadleaved forest, DBF -
631 deciduous broadleaved forest, ENF - evergreen needle leaved forest, DNF - deciduous needle
632 leaved forest, DSB - deciduous shrubs and HRB - herbaceous species. The data have also been
633 binned (bin size = 10), with the original data shown in a matching semi-transparent colour. In
634 panel (b) the box and whisker plots show the C_i value at the transition point (line, median; box,
635 inter-quartile range), with bars extending to 1.5 times the inter-quartile range. Dots outside of
636 the box and whiskers show outlying points.

637

638 Figure 3: Comparison between V_{cmax} values estimated from traditional A-C_i curve fitting and
639 V_{cmax} estimated from one-point method, $\hat{V}_{cmax}$. Panel (a) and (b) show the effect of using a
640 known and an estimated R_{day} (1.5% of V_{cmax}), respectively. Data shown are for all 1318 species
641 but have been coloured as in Figure 2 to match representative plant functional types. Regression
642 lines have been fit to the raw data (1318 species measurements) and coloured to match plant
643 functional types.

644

645 Figure 4: Residuals ($V_{cmax} - \hat{V}_{cmax}$) shown as a function of V_{cmax}, ambient g_s, estimated R_{day} and
646 C_i. Data were binned (panels (a) and (b) bin size = 10; panel (c) and (d) bin size = 0.05; panels
647 (e) and (f) bin size = 0.25), panels (e) and (f), bin size = 10), with the original data shown in a
648 matching semi-transparent colour. Data shown are for all 1318 species but have been coloured
649 as in Figure 2 to match representative plant functional types. A significant ($p<0.05$) trend in
650 the residuals is shown by a solid black line. Trend lines have been fit to the raw data (1318

651 species measurements). In panels (a) and (b) the grey dashed lines represent 5 (dot-dash) and
652 10% (dot-dot) error, respectively.

653

654 Figure 5: Residuals ($V_{cmax} - \hat{V}_{cmax}$) shown as a function of leaf temperature, mean annual
655 temperature and mean annual precipitation. Data in the residual panels have been binned
656 (panels (a), (b), (c) and (d) bin size = 0.5; panels (e) and (f), bin size = 100), with the original
657 data shown in a matching semi-transparent colour. Data shown are for all 1318 species, but
658 have been coloured as in Figure 2 to match representative plant functional types. A significant
659 ($p<0.05$) trend in the residuals is shown by a solid black line. Trend lines have been fit to the
660 raw data (1318 species measurements).

661

662 Figure 6: Fitted R_{day}:V_{cmax} ratio (a) and (b) R_{day} as a function of leaf temperature using the
663 Bernacchi *et al*. (2001) parameters. Data shown are for all 1318 species, but have been coloured
664 as in Figure 2 to match representative plant functional types. The horizontal red line shows the
665 R_{day}:V_{cmax} commonly assumed by terrestrial biosphere models following Collatz *et al*. (1991).

666

667 Figure 7: Relationship between V_{cmax} values estimated from the traditional approach and $\hat{V}_{cmax}$
668 values using three different sets of K_c, K_o, and Γ^* parameters. Data shown are for all 1318
669 species, but have been coloured as in figure 2 to match representative plant functional types.
670 Regression lines have been fit to the raw data (1318 species measurements) and coloured to
671 match plant functional types.

672

673 Supplementary Figure 1: Climatic space covered by this study shown by density hexagons.
674 Over-plotted colour symbols represent sampled species, grouped by plant functional type.

675

676 Supplementary Figure 2: Residuals ($V_{cmax} - \hat{V}_{cmax}$) shown as a function of a moisture index and
677 elevation. Data in the residual panels have been binned ((panels (a) and (b) bin size = 0.1;
678 panels (c) and (d), bin size = 100), with the original data shown in a matching semi-transparent

colour. Data shown are for all 1318 species, but have been coloured as in figure 2 to match representative plant functional types. A significant ($p<0.05$) trend in the residuals is shown by a solid black line. Trend lines have been fit to the raw data (1318 species measurements).

Supplementary Figure 3: Residuals $V_{cmax} - \hat{V}_{cmax}$) shown as a function of the number annual growing degree days above > 0°C and > 5°C, Data in the residual panels have been binned (panels (a), (b), (c) and (d) bin size = 0.5), with the original data shown in a matching semi-transparent colour. Data shown are for all 1318 species, but have been coloured as in figure 2 to match representative plant functional types. Significant ($p<0.05$) trends in absolute and non-absolute residuals are shown by the solid red and black lines, respectively. These trends lines have been fit to the raw data (1318 species measurements).

Supplementary Figure 4: Fitted R_{day}:V_{cmax} ratio (a) and (b) R_{day} as a function of leaf temperature using the Badger & Collatz (1977) parameters. Data shown are for all 1318 species, but have been coloured as in figure 2 to match representative plant functional types. The horizontal red line shows the R_{day}:V_{cmax} commonly assumed by terrestrial biosphere models following Collatz *et al*. (1991).

Supplementary Figure 5: Fitted R_{day}:V_{cmax} ratio (a) and (b) R_{day} as a function of leaf temperature using the Crous *et al*. (2013) parameters. Data shown are for all 1318 species, but have been coloured as in figure 2 to match representative plant functional types. The horizontal red line shows the R_{day}:V_{cmax} commonly assumed by terrestrial biosphere models following Collatz *et al*. (1991).

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Supporting Information

Additional supporting information may be found in the online version of this article.

Fig. S1: Climatic space covered by this study shown by density hexagons.

Fig. S2: Residuals ($V_{cmax} - \hat{V}_{cmax}$) shown as a function of a moisture index and elevation.

Fig. S3: Residuals $V_{cmax} - \hat{V}_{cmax}$) shown as a function of the number annual growing degree days above > 0°C and > 5°C.

Fig. S4: Fitted R_{day}:V_{cmax} ratio (a) and (b) R_{day} as a function of leaf temperature using the Badger & Collatz (1977) parameters.

Fig. S5: Fitted R_{day}:V_{cmax} ratio (a) and (b) R_{day} as a function of leaf temperature using the Crous *et al*. (2013) parameters.

TABLES

Table 1: List of the data sets, site locations, vegetation types and associated references used in this study.

Dataset	Site	Longitude	Latitude	References	Vegetation type
Ellsworth/Crous (51 species)	Aspen FACE, WI, USA	45.68	-89.63	Ellsworth *et al*., (2004)	Temperate broadleaf deciduous forest
	Blue Mountains, NSW, Australia	-33.71	150.55	Ellsworth *et al*., (2015)	Open eucalypt forest
	Cape Tribulation crane site, QLD, Australia	-16.10	145.45	Unpublished	Lowland tropical rainforest
	Carolina beach, NC, USA	34.05	-77.91	Unpublished	Temperate evergreen forest
	Carolina Lake, NC, USA	35.90	-79.09	Ellsworth *et al*., (2004)	Temperate needle-leaved deciduous forest
	Cedar Creek LTER, USA	45.41	-93.19	Crous *et al*., (2010)	Temperate savanna
	Cocoparra National Park, NSW, Australia	-34.17	146.23	Unpublished	*Callitris* pine woodland
	Driftway Cumberland Plain, Richmond, NSW, Australia	-33.62	150.74	Ellsworth *et al*., (2015)	Open eucalypt forest
	Duke Forest, NC, USA	35.97	-79.10	Ellsworth et al., (2004); Ellsworth *et al*., (2012)	Temperate evergreen forest
	Endla bog, Endla, ESTONIA	58.86	26.17	Niinemets *et al*. (2001)	Boreal evergreen bog
	Hawkesbury, Richmond, NSW, Australia	-33.61	150.74	Crous *et al*., (2013); Ellsworth *et al*., (2015)	Open eucalypt forest
	Illawarra, Robertson, NSW, Australia	-34.62	150.71	Ellsworth *et al*,. (2015)	Wet sclerophyll forest
	Kuring-Gai National Park (Murrua Track), NSW, Australia	-33.69	151.14	Unpublished	Open eucalypt forest
	La Sueur National Park, WA, Australia	-30.19	115.14	Ellsworth *et al*., (2015)	Kwongan woodland
	Nevada Test Site, NV, USA	36.77	-115.97	Ellsworth *et al*., (2004)	Mojave desert
	Saginaw forest, MI, USA	42.27	-83.81	Unpublished	Temperate broadleaf deciduous forest
	UMBS Pellston, MI, USA	45.56	-84.72	Unpublished	Temperate broadleaf deciduous forest

Commented [K4]: Shouldn't this need to add up to the 1318 species?

	Mill Haft, Staffordshire, UK	52.80	2.30	Unpublished	Temperate broadleaf deciduous forest
JACARE (366 species)	Allpahuayo, Loreto, Peru (~100 m asl)	-3.95	-73.44	Atkins *at al*, 2015; Malhi *et al*., unpublished.	Humid Amazonian lowland forest
	Cuzco Amazonico, Peru	-3.37	-72.97	Malhi *et al.*, 2014; Anderson *et al*, 2009	Forests over alluvial terrain
	Esperanza, Peru	-2.48	-71.97	Girardin *et al.*, 2014a, b	Upper limit of the cloud forest
	Jenaro Herrera, Peru	-4.88	-73.63	del Aguila-Pasquel *et al.*, 2014	Humid Amazonian lowland forest
	San Pedro, Peru	-6.54	-77.71	Huasco *et al.*, 2014	Cloud forest
	Sucusari, Peru	-3.25	-72.91	Atkins *et al*., 2015	Humid Amazonian lowland forest
	Tambopata, Peru	-13.02	-69.60	Huasco *et al.*, 2014	Humid Amazonian lowland forest
	Trocha Union, Peru	-13.03	-71.49	Huasco *et al.*, 2014	Montane cloud forest
	Wayquecha, Peru	-13.12	-71.58	Girardin *et al.*, 2014a, b	Upper limit of the cloud forest
Togashi (51 species)	Great Western Woodland, WA, Australia	-30.25	-30.25	Unpublished	Temperate eucalyptus woodland
	Robson Creek, QLD, Australia	-17.25	145.75	Unpublished	Tropical rainforest
TROBIT (44 species)	Asukese, Ghana	7.14	-2.45	Domingues *et al.* (2010)	Humid tropical lowland forest
	Bissiga, Burkina Faso	12.73	-1.16	Domingues *et al.* (2010)	Tropical woody savanna
	Bissiga, Burkina Faso	12.73	-1.17	Domingues *et al.* (2010)	Tropical woody savanna
	Boabeng-Fiema, Ghana	7.71	-1.69	Domingues *et al.* (2010)	Seasonal tropical forest
	Dano, Burkina Faso	10.94	-3.15	Domingues *et al.* (2010)	Open tropical savanna
	Hombori, Mali	15.34	-1.47	Domingues *et al.* (2010)	Dry grass savanna
	Kogyae, Ghana	7.30	-1.18	Domingues *et al.* (2010)	Tropical woody savanna
Serbin (21 species)	Coachella Valley Agricultural Research Station, CA, USA	33.52	-116.16	Serbin *et al*., (2015)	Vineyard and date palm
	Loma Ridge Coastal Sagescrub EC site, CA, USA	33.73	-117.70	Unpublished	Coastal sage-scrub

	Sierra Mixed Conifer EC site, CA, USA	37.07	-119.20	Unpublished	Mixed conifer/broadleaf forest
	San Joaquin Experimental Range, CA, USA	37.08	-119.73	Unpublished	Semi-arid woodland
	San Jacinto James Reserve EC tower site, CA, USA	33.81	-116.77	Unpublished	Mixed conifer/broadleaf forest
	UW-Madison Arboretum, WI, USA	43.04	-89.43	Unpublished	Temperate broadleaf deciduous forest
Domingues (24 species)	Tapajós, Brazil	-3.75	-56.25	Domingues *et al.,* (2005)	Humid Amazonian lowland forest
Niinemets (3 species)	Ülenurme, Estonia	58.30	26.70	Niinemets (1998)	Temperate broadleaf deciduous forest
Rogers (7 species)	Barrow Environmental Observatory, Barrow, AK, USA	71.32	156.62	Unpublished	Tundra
Tarvainen (1 species)	Skogaryd, Sweden	58.23	12.09	Tarvainen *et al.,* (2013)	Hemi-boreal coniferous forest

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Table 2: Three sets of temperature dependencies for the Michaelis constant for CO_2, K_c (µmol mol^{-1}) and the Michaelis constant for O_2, K_o (mmol mol^{-1}) and the CO_2 compensation point, Γ^* (µmol mol^{-1}). T_k is the leaf temperature in Kelvin, R is universal gas constant (8.314 J mol^{-1} K^{-1}) and O_i is the intercellular concentrations of O_2 (210 mmol mol^{-1}).

Reference	Badger and Collatz (1977)	Bernacchi et al. (2001)	Crous et al. (2013)
Environment	*in vivo*	*in vivo*	*in vitro*
Species	Bracted orache (*Atriplex glabriuscula)*	Tobacco (*Nicotiana tabacum*)	Tasmanian blue gum (*Eucalyptus globulus)*
K_c	If $T_k > 288.15$: $460 \cdot exp\left(\frac{59536(T_k - 298.15)}{298.15 \cdot R \cdot T_k}\right)$ else if $T_k < 288.15$: $920 \cdot exp\left(\frac{10970(T_k - 298.15)}{298.15 \cdot R \cdot T_k}\right)$	$404.9 \cdot exp\left(\frac{79403(T_k - 298.15)}{298.15 \cdot R \cdot T_k}\right)$	Same as Bernacchi *et al*. (2001)
K_o	$330 \cdot exp\left(\frac{35948(T_k - 298.15)}{298.15 \cdot R \cdot T_k}\right)$	$278.4 \cdot exp\left(\frac{36380(T_k - 298.15)}{298.15 \cdot R \cdot T_k}\right)$	Same as Bernacchi *et al*. (2001)
Γ^*	$\frac{K_c \cdot O_i \cdot 0.21}{2 \cdot K_o}$	$42.75 \cdot exp\left(\frac{37830(T_k - 298.15)}{298.15 \cdot R \cdot T_k}\right)$	$38.892 \cdot exp\left(\frac{20437(T_k - 298.15)}{298.15 \cdot R \cdot T_k}\right)$

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